Application of Cepstrum Analysis and Linear Predictive Coding for Motor Imaginary Task Classification

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***Abstract*—In this paper, classification of electroencephalography (EEG) signals of motor imaginary tasks is studied using cepstrum analysis and linear predictive coding (LPC). The Brain-Computer Interface (BCI) competition III dataset IVa containing motor imaginary tasks for right hand and foot of five subjects are used. The data was preprocessed by applying whitening and then filtering the signal followed by feature extraction. A random forest classifier is then trained using the cepstrum and LPC features to classify the motor imaginary tasks. The resulting classification accuracy is found to be over 90%. This research shows that concatenating appropriate different types of features such as cepstrum and LPC features hold some promise for the classification of motor imaginary tasks, which can be helpful in the BCI context.**

Keywords—BCI; cepstrum analysis; EEG; filetring; LPC; random forest.

I. Introduction

With the increasing number of research in the BCI field, understanding of the brain waves is gaining huge importance. BCI or Brain-Machine Interface (BMI) and its application has become one of the hot research topics with the advances in technology aiming to make lives of people easier. A BCI system allows to communicate with others or to generate control signals for controlling devices such as machines, electric wheelchair [1, 2], artificial limbs or robots [3-6] by utilizing the brain's neural activity without requiring any muscle control or direct physical movement [7-10]. The major focus and emphasis of BCI research is in the field of biomedical engineering [11-15].

BCI could be beneficial in restoring valuable functions of severely disable people. The first BCI application was developed in 1964 [16] by Grey Walter. The application used EEG recordings for controlling a slide projector. With technological advancements, devices having low cost and reduced complexity such as Neurosky Mindwave [17] device and Emotiv EPOC/EPOC+ headset [18] have been developed, which are widely accepted and used in BCI research and applications.

BCI systems based on EEG signal have gained widespread interest due to their potential uses. The EEG signal is recorded using non-invasive sensors making it safer and easy to use. However, the EEG signal is contaminated by other noises such as Electrocardiogram (ECG), Electrooculogram (EOG) and Electromyogram (EMG). Adaptive filters and blind source separation (BSS) techniques [19, 20] can be utilized to effectively remove the EOG and ECG artifacts. For the removal of muscular artifacts, researchers have explored the use of ICA [21-23], a BSS technique.

A BCI system usually involves these processes: data acquisition, preprocessing, feature extraction and classification (for the purpose of generating control signals). Preprocessing is done on the acquired signal to remove the noise/artifacts. For feature extraction, a number of feature extraction techniques such as power spectral density (PSD), R (ratio of α and β activities) [24], Common Spatial Pattern (CSP) [25, 26], statistical features, Self-Organizing Maps (SOM), Fractal Dimension (FD), correlation, Granger causality, spectral coherence [27] and information entropy [28, 29] have been studied. A number of classifiers such as support vector machine (SVM) [24, 30-36], K-Nearest Neighbors (KNN) [37-39], Random Forest (RF) [40], etc. have been used. SVM and Linear classifiers [41-44] have also been widely used for other applications.

All the above research works have contributed positively to the field of BCI. However, to the authors knowledge no research has been carried out to study the use of cepstrum and LPC features for EEG signal classification of motor imaginary tasks. In this research, the widely used speech recognition feature extraction methods; cepstrum analysis and LPC will be studied and applied for the classification of EEG signals. A random forest classifier will be used for classification. Various feature extraction methods have been proposed and studied. However, feature extraction techniques such as canonical correlation analysis, common spatial spectral pattern (CSSP) and common sparse spectral spatial pattern (CSSSP) [45] are computationally expensive. Therefore, the computational time for feature extraction can be reduced by the use of LPC features.

This paper is organized as follows. In section II, a brief description of related literature works that have been carried out is presented. Section III presents the description of the dataset used and the proposed method respectively. In section IV, the results are presented while section V concludes the important findings of this paper.

II. RELATED WORKS

In the realization of an EEG-based BCI system, generally three phases are involved: (i) recording the brain activity by placing electrodes located on the scalp and pre-processing the recorded brain wave (EEG signal) for artifact removal, which improves the signal-to-noise ratio (SNR); (ii) feature extraction from the pre-processed EEG signal in order to obtain meaningful information; (iii) classification of the signals using the features in order to translate them into control commands and drive external devices. Several EEG-based BCI applications such as wheelchair controllers [2, 46], and word speller programs [47] have been successfully developed. A BCI system can be employed for various reasons such as to understand our mental states and to control devices via thought without any muscle activity. Automatic emotion recognition [30, 48] is one such application, which potentially bridges the gap between human and machine interactions.

A number of researchers have proposed different noise removal and feature extraction techniques. The common artifact removal methods are adaptive filters and BSS technique. A Cycle Spinning Wavelet Transform ICA (CTICA) method for denoising the EEG signal is presented in [49]. The authors argue that it is the most accurate separation method. The method uses cyclic spinning and merges Translational Invariant Wavelet Transform (TIWT), Unscented Kalman Filter (UKF) and ICA. The method outperformed Fast ICA and Efficient Fast ICA (EFICA).

Novi et. al. [26] proposed a sub-band common spatial pattern (SBCSP) method for feature extraction aiming to tackle the problem of varying rhythmic patterns between different subjects. The EEG signal is decomposed into sub-bands using a filter bank. Then a discriminative analysis is used for extracting the SBCSP features. A Linear Discriminant Analyzer (LDA) with the SBCSP features as the inputs is used to obtain scores. The classification capability of each frequency band is reflected by these scores. The scores are then fused, using Recursive Band Elimination (RBE) and Meta-Classifier (MC), for making a decision. The BCI competition III dataset IVa have been used to assess the performance of the SBCSP method. Other methods that have been proposed in the literature for selecting the optimal frequency bands automatically are common spatial pattern (CSP), CSSSP [45], discriminative filter band CSP (DFBCSP) [50], and adaptive filters.

LPC features have been widely used in speech recognition and its use and effectiveness for EEG signal classification will be studied in this research. In [51], the authors combined the Mel Frequency Cepstral Coefficients (MFCC) with LPC features for the purpose of speaker identification. Ten LPC and twelve MFCC features are extracted from each sample. An artificial neural network (ANN) has been used for recognition and identification of the speech signal. In [52], a new hybrid method for optimizing the extraction of accent in ethnically diverse Malaysian English from speech utterances over facets using LPC obtained from DWT is proposed. Using hybrid dyadic-X DWT-LPC features attained an increase of 9.28% classification accuracy compared to the conventional LPC method. In [53] and [54], LPC features have been used for emotion recognition (in Romanian Language) and speaker recognition respectively.

III. METHODOLOGY

A. EEG Data Description

Dataset IVa from BCI competition III, which is provided to the public by Fraunhofer FIRST (Intelligent Data Analysis Group) have been used [55, 56]. The dataset IVa consists of EEG signals for motor imaginary tasks, namely right hand and left foot. It contains the EEG signals from 118 channels at positions of the extended international 10/20 system [57], which are recorded from five subject's referred to as *aa*, *al*, *av*, *aw* and *ay*. The signal was sampled at 1000 Hz. However, the down sampled signal at 100 Hz is used. Each subject performed 280 trials having equal number of trials from each of the two motor imaginary tasks. From the 118 channels of data, only the following 24 channels data is used (Fp1, Fp2, F3, F4, F7, F8, FC3, FC4, FT7, FT8, T7, T8, P3, P4, P7, P8, C3, C4, CP3, CCP4, TP7, TP8, O1, O2). This down sampled signal of 24 channels is used for further processing and is referred to as data from here onwards.

B. Pre-processing, Feature Extraction and Classification

The overall block diagram of the proposed method is shown in Fig. 1. The data was firstly centered to make its mean zero followed by the whitening process. The whitened signal is then normalized and passed through five bandpass filter banks namely theta (0-4 Hz), delta (4-8 Hz), alpha (8-14 Hz), beta (14-30 Hz) and gamma (30-50 Hz). Windowing is then applied to the filtered data having a window size of 0.80 seconds with an overlap of 75 percent. The LPC and cepstrum features are then extracted from each of the window data.

In LPC, the signal is approximated as a linear combination of past p samples of the signal, where p represents the order of prediction. The predicted signal $\hat{s}(n)$ of the present sample $s(n)$ is obtained from the past samples using (1).

$$\hat{s}(n) = -\sum_{k=1}^{k=p} a_k s(n-k) \tag{1}$$

Cepstrum coefficients are obtained by taking the inverse Fourier transform of the logarithm of the magnitude spectrum of the signal. All processing is carried out in MATLAB except for the training and testing phase, which is carried out using WEKA.

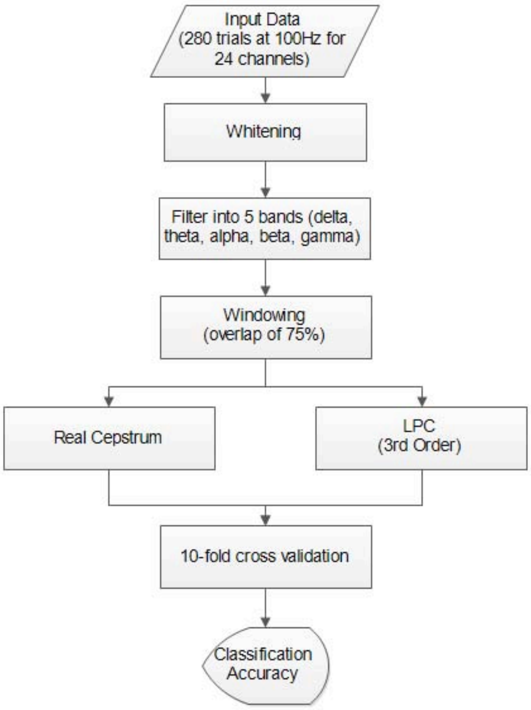

Fig. 1. Proposed cepstrum + LPC feature extraction method.

The MATLAB signal processing toolbox functions *lpc* and *rceps* are used to perform the 3rd order LPC and real cepstrum analysis, respectively. LPC coefficients C_1, C_2 and C_3 are used as features while C_0 is ignored. When real cepstrum is performed, the cepstrum coefficients and the unique phase sequence is obtained. The maximum and minimum of the unique phase sequence is used as features. Therefore, each feature vector is 24 (channels) x 5 (bands) x 5 (features: 3 LPC features and 2 cepstrum features), which gives a total of 600 features for each windowed data.

Finally, the feature vectors are fed to a random forest classifier to train and test the accuracy of the trained classifier model.

IV. Results and Discussions

A range of window sizes (0.50s, 0.80s, 1.00s, 1.50s and 2.00s) and overlap (25%, 50% and 75%) have been tested. However, window size of 0.80s and overlap of 75% produced the optimal results and are hence used in the pre-processing stage. Three separate experiments were carried out in order to evaluate and show the significance of the fusion of LPC and cepstrum features. The feature vectors [(i) with three LPC features; (ii) with two cepstrum features; (iii) with LPC and cepstrum features concatenated together] are fed as the input to the random forest classifier (various classifiers such as SVM, random committee, and rotation forest have been tested however random forest gives the best result and thus have been used in this paper). Different number of LPC features have been tested however using only three LPC coefficients gave similar results compared to using 12 LPC coefficients as features. Hence only three LPC coefficients have been used as LPC features in this work. 10-fold cross validation (with 80% of data used as training data and 20% as test data) is used for evaluating the performance of each of the feature extraction methods. For each subject, ten trial runs were carried out and the averages of the results obtained were taken. The average accuracies (across the five subjects) of the ten trial runs for the three experiments is plotted in Fig. 2. It can be noted that for subjects *aa* and *al*, the classification accuracies of the method with the cepstrum and LPC features concatenated are a little less than that of using only cepstrum features. However, for the other three subject (*av*, *aw* and *ay*) it is quite evident that the fusion of the cepstrum and LPC features results in an increase in the classification accuracy as the results are greater than that of classification accuracies obtained when only cepstrum or LPC features are used. The fusion of the cepstrum and LPC features shows that the average of all five subjects' classification accuracy increases by 2% to 4% with respect to that of when only cepstrum or LPC features are used.

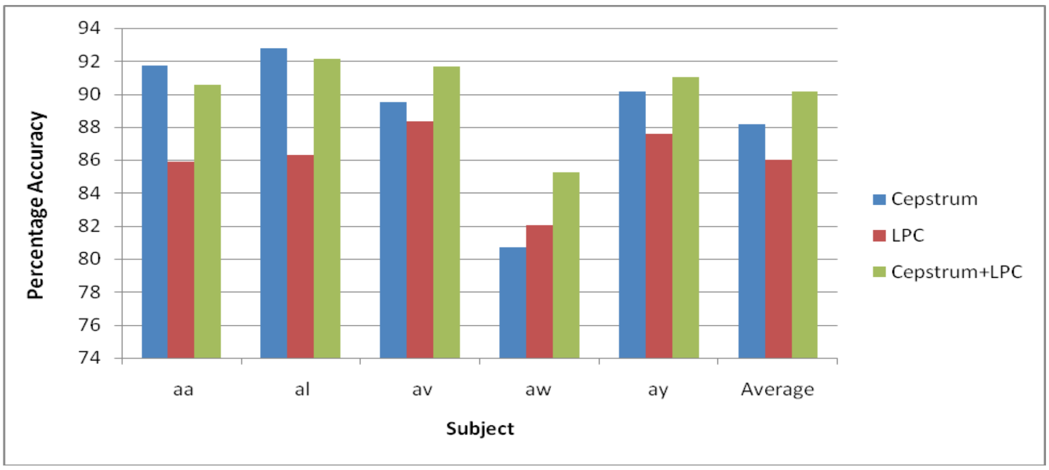

Fig. 2. Average 10-fold cross validation accuracies of all subjects.

TABLE I. 10x10-FOLD CROSS VALIDATION ERRORS OF DIFFERENT METHODS

No.	Method	Window Size (seconds)	Classifier	Percentage (%) Classification Error					
				Subject aa	***Subject al***	***Subject av***	***Subject aw***	***Subject ay***	***Average***
1	CSSSP [45]	2	SVM	11.6 ± 6.3	2.1 ± 2.7	31.8 ± 7.7	6.5 ± 4.5	10.5 ± 5.7	12.50
2	RBE [26]	2	SVM	9.2 ± 4.5	2.2 ± 3.4	31.0 ± 7.3	4.2 ± 3.3	5.0 ± 3.4	10.30
3	FBCSP [50]	2	SVM	6.93 ± 0.58	0.97 ± 0.24	31.0 ± 1.42	4.90 ± 0.89	6.18 ± 0.97	9.99
4	CSP+DS [45]	2	SVM	7.3 ± 5.1	0.9 ± 1.9	22.5 ± 7.8	2.8 ± 3.1	5.5 ± 4.3	7.80
5	Sparsity-aware [58]	2	SVM	19.64 ± 12.81	4.64 ± 4.48	28.93 ± 7.08	2.14 ± 1.96	6.43 ± 2.99	12.36
6	Cepstrum+LPC	0.8	RF	9.44 ± 0.96	7.87 ± 0.78	8.32 ± 0.61	14.76 ± 0.82	8.97 ± 0.53	9.87

In Table 1, the error rates of all five subjects together with the average error of the proposed cepstrum+LPC feature extraction method is shown along with other methods that have used the same dataset for performance evaluation. From the results obtained, it can be analyzed that the use of only cepstrum or LPC features does not give very promising results and the average individual error rates are higher than other feature extraction methods depicted in Table 1. All the other methods have used a window size of 2s with SVM as the classifier. However, 10-fold cross validation is used by all methods to evaluate the performance in terms of classification errors. It is noted that compared to other methods the average classification error of the proposed cepstrum+LPC feature extraction method does not give the best results however, the results are promising. The method outperforms the CSSSP, RBE, and FBCSP feature extraction methods. Analyzing the results for the individual subjects, the cepstrum+LPC method gives optimal results for subject *av*. For subjects *aa*, *al*, *aw* and *ay* the classification error rate of the proposed cepstrum+LPC method is not the best. However, the individual subject results are also promising. The proposed method performed worst for subject *aw* having a classification error of 14.76% while the best performance was noted for subject *al* having an error rate of 7.87%. Cepstrum and LPC features are computationally less expensive compared to other methods such as CSP, CSSSP, and FBCSP. Usually the data transfer rate in BCI applications is slow. Therefore, a smaller window size would be also advantageous when real time implementation is required.

The size of each feature vector used in this research as mentioned is 600. To reduce the dimensionality of the feature vectors, the widely used principle component analysis (PCA) [59] and linear discriminant analysis (LDA) [60-63] can be applied. Dimensionality reduction has not been carried out in this research and will be considered later.

V. CONCLUSIONS

In this work, it is shown that speech processing features such as cepstrum and LPC can be applied to the field of biomedical signal processing. The results obtained are promising and provides the basis for further research in the use of speech processing features for biomedical signal classification.

Some post-processing techniques such as cepstral weighting, cepstral mean subtraction (CMS), pole-filtered cepstral mean subtraction (PFCMS), adaptive component weighted cepstrum (ACWC), and post-filter cepstrum have not been used, and will be addressed and evaluated later by expanding the proposed method. Also, the use of MFCC features will be studied.

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